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A temporal perspective on repeated ties across university-industry R&D consortia

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Abstract

Divergent time norms between participating organizations constitute a central barrier to cross-sectoral collaborations. We unpack this tension by studying two distinct time-utilization strategies of university and industry in 1,845 R&D consortia. The paper shows that collaborating organizations that are subject to divergent time norms can shift the time focus in their favor through the strategic timing of repeated ties. If university-industry consortia are repeated, this repetition tends to take place either at the beginning of the consortium (parallel timing) or at the end (sequential timing) but typically not in the middle. Industry partners seek to “compress time” by working on different consortia in parallel and therefore want to repeat a collaboration early, whereas universities seek to “extend time” through sequential timing of consortia, i.e., repeat a collaboration at the end or after a consortium has ended. We provide a qualitative substantiation of the identified time-utilization strategies and show that both options coexist in multipartner consortia.

Keywords:

University-industry collaboration; Repeated collaboration; Time norms and timing preferences; Multipartner R&D-consortia; Collaboration barriers

1. Introduction

Both university partners (Meyer-Krahmer & Schmoch, 1998) and industry partners (Bruneel, D'Este & Salter, 2010) have indicated that the single most prominent barrier to university-industry collaboration results from distinct time norms. Synchronizing time norms, i.e., the pace of working and perceptions of when things should be done, is a difficult managerial challenge (Dille & Söderlund, 2011; Shi, Sun, & Prescott, 2012). Whereas the academic time norm is derived from (long-term) time-to-journal publication and dissertation completion (Niedergassel & Leker, 2011), the industrial time norm is driven by (short-term) time-to-market considerations under competitive pressures (Bjerregaard, 2010). The difficulty of reconciling university and industry time norms in a single collaboration raises questions as to whether and how this is done in *repeated* collaboration.

We focus on repeated university-industry collaboration because the innovation benefits of university-industry collaborations (e.g., Hagedoorn, Link, & Vonortas, 2000; Perkmann et al., 2013, Szücs, 2018) often do not materialize in the first joint consortium. The studied consortia are collaborative entities, including one university partner and one or more industry partners. Due to the high risks of innovation trajectories and the rather distinct orientations of university and industry partners (Meyer-Krahmer & Schmoch, 1998), the first consortium generally serves as a testing ground for exploring the partners' collaboration potential. Repeated collaboration, or the joint participation of consortium members in a second consortium, has been introduced as a solution to this problem. Repeated collaboration implies buying time to explore mutual fit and to align expectations before reaping the benefits of a partnership (Bruneel et al., 2010; Hewitt-Dundas, Gkypali, & Roper, 2019). However, this solution is at risk if university and industry partners differ in their preferences regarding *when* and *with whom* to repeat a collaboration.

Prior studies on this time-norm tension were limited by their reliance on qualitative evidence of distinct time norms (e.g., Bjerregaard, 2010; Hagedoorn et al., 2000) or perception ratings (Bruneel et al., 2010; Meyer-Krahmer & Schmoch, 1998). Our research setting and the data on the composition and timing of university-industry R&D consortia over 24 years in provide the opportunity to conduct a longitudinal quantitative analysis of the actual collaborative behavior of the parties involved (cf. Hmieleski & Powell, 2018, Perkmann et al., 2013). The dataset allows us to analyze how the different time norms manifest themselves in the repeated collaboration strategies that university and industry each use to shift the time focus in their favor. Moreover, the dataset allows us to compare time-utilization strategies across different configurations of actor sets that repeat their collaborations over time: university-industry versus industry-industry; dyadic versus multipartner. Accordingly, this study addresses the following question: *How is the likelihood of repeated ties distributed over time and to what extent is the timing of repeated ties different for distinct types of involved actor sets?*

Event history analysis on the timing of repeated ties across 1,845 university-industry R&D consortia shows that if consortia are repeated, the repetition typically occurs either at the start of the consortium (parallel timing) or at the end (sequential timing) but not usually in the middle. Moreover, university partners tend to push for “time extension” through sequential consortia, while industry partners preferably work in parallel consortia to “compress time”. Complementary interviews reveal that industry’s time compression strategy is associated with gaining knowledge breadth, synergy, and first-mover advantages, whereas university’s time extension strategy is associated with gaining knowledge depth, learning and evaluative insights over time, as well as with feasibility. However, the observation that both time-utilization strategies coexist instead of blending in multipartner consortia signals how difficult it is to resolve the time-norm tension. In

the following, we present the theoretical argument, methodology, findings, and a discussion on the implications of the study.

2. Theoretical background

Our theory section reviews the literature on the timing of repeated collaboration and the literature on the composition of actor sets involved in university-industry collaboration. We develop a taxonomy of repeated collaboration that connects the two literatures by combining the timing and composition of actor sets. The taxonomy serves to explain how time norms within university-industry consortia can indeed conflict or how they can be reconciled. The taxonomy is the basis for our hypothesis.

2.1. *Timing of repeated collaboration*

We define repeated collaboration as the continuation of collaboration in two subsequent consortia at t_0 and t_n , in which the *repeating actor set* at t_n consists of a subset ranging between a minimum of two organizations in the consortium present at t_0 and a maximum of all organizations in the consortium at t_0 . In line with prior research, Hewitt-Dundas and colleagues argue that “[...] it is through repeated collaboration that routines are established on issues such as research targets, dissemination of results and timing of deliverables. These routines reduce attitudinal (orientation-related) barriers to collaboration for both business and university partners and may also have a – more limited – effect on reducing transaction-related barriers to collaboration, e.g., agreement on intellectual property (IP) issues” (2019, p. 4).

Hitherto, little academic attention has been devoted to the timing of repeated ties. A notable exception is Gulati (1995), who argues that the likelihood of repeated collaboration gradually increases over time until a threshold is reached near the consortium’s end, after which the

likelihood decreases again. “Information about another firm's reliability as a partner, its operations, and possible alliance opportunities becomes available *only once an alliance is in place*. Hence, *over time*, each firm acquires more information and builds greater confidence in the partnering firm. Concomitant with this process is an increase in the likelihood of a new alliance. [...] this effect gives way to diminishing information *as past alliances end*, and the momentum for forming new alliances declines” (1995, pp. 643-644, emphases added).

Building on Gulati (1995), we distinguish two strategies for the timing of repeated ties. Sequential timing of repeated collaboration means that a subset of consortium partners starts a new joint consortium no earlier than after the termination of another consortium; thus, repeated collaboration occurs in a *sequential* fashion. The sequential timing of repeated collaboration represents a *time extension strategy*. When a consortium lasts four years and is repeated in year five – after the termination of the first consortium in its fourth year – the consortium uses up all available time until its contract expires; only then does it start a new consortium. We elaborate Gulati's view on the timing of repeated ties by adding *parallel* timing, wherein consortium members start a second consortium shortly after the start of the first one. Parallel timing of repeated collaborations within the time window of ongoing consortia supports the quick ramp-up of R&D activities. Parallel timing intensifies the collaboration, depending on both the number of consortia started in parallel and the stage at which the repetition occurs. The earlier parallel consortia are initiated after the start of the initial joint consortium, the more overlap is organized in parallel consortia and the higher the collaboration intensity. It represents a *time compression strategy*, literally ramping up the volume of joint activities compressed within a limited amount of time.

During the start-up phase of the consortium, university and industry partners debate the core research problem. In this phase, participants gain swift partner-specific experience (Das & Kumar,

2007), which can provide a solid basis for starting multiple projects in quick succession; i.e., the parallel timing of repeated collaboration. Once these projects start, partners must first master the content, resulting in basic scientific findings. During this period of project execution, the consortium shifts attention from partner-specific learning to content learning (Das & Kumar, 2007). Repeating the consortium has little value in this period, as most consortia do not generate new applicable knowledge at such a short notice. However, when the consortium ends actors evaluate its outcomes (Das & Kumar, 2007), arousing interest in new research projects and opening up options for sequential repeated collaboration. After the consortium ends, momentum for repeated collaboration evaporates quickly because (former) consortium members no longer have direct interactions (Amburgey et al., 1993; Gulati, 1995). Figure 1 shows two distinct patterns of the timing of repeated collaboration: sequential versus parallel.

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 Insert Figure 1 about here

2.2. Composition of the actor set in university-industry consortia

The question of when to repeat a consortium, either in parallel or sequentially, is strongly related to the question of with whom to repeat, referring to the configuration of involved actors. Recent research has shown that organizations are subject to substantially different time norms (e.g., Dille & Söderlund, 2011; Reilly, Souder, & Ranucci, 2016; Shi et al., 2012). “[...] timing norms are seen as important organizing elements that govern activities in the sense that they impose implicit cycles of rhythms and provide explicit schedules and deadlines to which the involved actors need to respond. Thus, the timing norms for different actors involved in an inter-institutional project could be quite diverse and, in some cases, fundamentally conflicting” (Dille & Söderlund, 2011, p. 486).

In this study, consortia always consist of a university partner (consortium leader) and at least one – but frequently more than one – industry partner (consortium member). Consortia consist of a minimum of two partners but can also include three or more. Repeated collaboration can be either a dyadic or a multiparty partnership. Figure 2 presents a two-dimensional repeated tie taxonomy that addresses the type of repeating actors (university-industry versus industry-industry) and the number of actors (dyad versus multipartner). Gray circles represent the (academic) consortium leader, white circles the industry partners (consortium member). It is important to note that the taxonomy only concerns the repeating actors (solid circles in Figure 2) and not the single-time (new or transient) consortium members (dashed circles). For example, repeated *industry-industry* collaboration (on the right side of Figure 2) involves two or more industry partners (solid circles) that participate in two consortia with different (nonrepeating) academic consortium leaders (dashed circles). Repeated *university-industry* collaboration (on the left side of Figure 2) relates to a university partner that participates in two consortia with at least partially the same industry partners.

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 Insert Figure 2 about here

2.3. *Time norms of university and industry*

Two processes matter for the understanding of time norms in relation to the timing of repeated ties: a process that aligns different time norms for the time being and a process that makes differences in time norms more salient. University and industry partners agree to engage in consortia that last an average of four years and lead to the dissertation of a PhD student. In that respect, the partners synchronize their time clocks. A shared time pressure for both partners pertains to “[the] key characteristic of technological opportunities [is] that they are often

temporary: the party that discovers an opportunity needs to exploit the opportunity quickly before the information reaches others in the field, or before the opportunity is replaced with a technologically more advanced one” (Katila & Mang, 2003, p. 317).

Despite this commonality and the agreement to collaborate in a time-bound setting for four years, universities and industry do adhere to different time norms for R&D activities: time-to-market for the industry partners and time-to-journal publication for the university partners in the consortium (e.g., Bruneel et al., 2010; Hmieleski & Powell, 2018; Meyer-Krahmer & Schmoch, 1998). In universities, publishing is usually essential to building one’s career; publications make a reputation (Niedergassel & Leker, 2011). Bjerregaard (2010, p. 104) describes the experience of the industry partner in university-industry collaboration: “They have to deliver reports and articles, but we must deliver products. They strive for perfection, where we require applicability. Fundamentally, many of our value sets do not match. It is not impossible to unite them, but we will also like to have applicability which is founded on front research and which is well tested. (...) But we would indeed have liked more commercial thoughts at the university before we met.” Bjerregaard (2010) infers that the conflicting logics give rise to competing conceptions of time. Consequently, university researchers attempt to extend the consortium period for the R&D work to ensure they achieve the research quality required for scientific publication, whereas the industry partner is looking for what the university has available off the shelf, readymade for commercialization. Industry partners continuously pursue the “reduction of new product development cycle time, [as] improvements in product performance have become strategic objectives for many technology-driven firms” (Cohen, Eliashberg & Ho, 1996, p. 173) despite the trade-offs with product quality. Reducing the duration of R&D cycles puts even more constraints on R&D collaboration between partners that operate according to distinct time norms. While

coping with competitive pressures, “[...] companies mostly need to consider time in terms of meeting short-term goals, [whereas the time norms] in the academic world are often much longer and less well defined” (Niedergassel & Leker (2011, p. 143). Not surprisingly, several researchers have argued that the different time norms of partners in R&D consortia cause problems in the management of R&D (Hagedoorn et al., 2000). In the following section, we discuss the distinct time norms in relation to our repeated tie taxonomy.

2.4. Hypothesis

In the case of *repeated industry-industry collaboration*, industry partners repeat their collaborations with different academic consortium leaders, applying industry time norms in this process. Relative to university-industry consortia, industry-industry consortia are more likely to pursue time compression through the parallel timing of repeated collaboration, as the time norms used in industry push harder for first-mover advantages that imply the shortening of new product development cycles and a stronger need to ramp up R&D intensity. Whether this industry-industry collaboration consists of two or multiple industry partners might have little impact on timing because all repeating actors come from industry and share the same time norms.

In contrast, for *repeated university-industry collaboration*, the distinction between dyadic and multipartner collaboration is rather decisive. It implies that the *same* university partner acting as consortium leader is present in two subsequent consortia with either one or multiple repeating industry partners. At first glance, the proportion of university partners vis-à-vis industry partners in the repeating actor set might determine the dominant time norm according to which a repeating actor set operates (Balconi & Laboranti, 2006; Meyer-Krahmer & Schmoch, 1998). This means that in the case of dyadic university-industry collaboration, parties might blend their time norms

(Besharov & Smith, 2014), while a repeating actor set including one university and two or more industry partners might follow the dominant industry time norm. However, in the research setting of this study, the influence of university and industry partners on the time norm is unequally distributed because an individual university partner coordinates the consortium and might therefore have a much stronger influence on the time norm compared to industry partners. It is the academic consortium leader who most likely initiates the consortium and – by virtue of his or her formal responsibility – plays a central role with respect to the goal setting and time orientation of the consortium. Hence, a repeating academic consortium leader most likely pushes for time extension by means of sequential timing of repeated collaboration, especially when only one industry partner is involved (*dyadic* university-industry collaboration). Therefore, we hypothesize the following:

Hypothesis: (a) Dyadic university-industry actor sets are more likely to pursue sequential timing of repeated collaboration, whereas (b) dyadic and multipartner industry-industry actor sets are more likely to pursue parallel timing of repeated collaboration.

In the case of *multipartner* university-industry consortia, it is less clear which time norm will be deployed because the dominant position of the university as a consortium leader is curtailed when industry partners outnumber the university partner. After all, multipartner university-industry consortia include one academic consortium leader but at least two industry partners. Whether it is the central role of the academic consortium leader or the larger number of industry partners that tips the balance regarding the dominant time norm cannot be determined in advance. Therefore, we apply an explorative approach to study the timing of multipartner university-industry repeated collaboration.

3. Methodology

3.1. Data

This study uses a longitudinal analysis of the establishment of 1,845 multipartner R&D consortia in an observation period of 24 years (1981-2004). All consortia consist of an academic consortium leader affiliated with a Dutch university, predominantly technical universities or science departments of general research universities, and a member committee consisting of, on average, 4 to 5 representatives of industrial firms or service providers. The consortium leader and members meet at least twice a year to evaluate the consortium's progress. Repeated collaboration concerns the joint participation of (a subset of) the members of one consortium in a second consortium. To identify the timing of repeated collaboration, consortia are observed 5 years after their start and 5 years after the consortium ends.

All consortia carry out publicly funded R&D projects financed by a long-standing Dutch technology program that facilitates R&D collaboration between university and industry. We derived the data from statutory annual evaluation reports, including descriptions of the consortium goal, members, the consortium's start and end, etc. This research context provides an ideal opportunity to investigate the timing of repeated collaboration because (I) the consortia are funded only if the composition of consortia fits the minimum funding requirements needed to stimulate collaboration; (II) repeated collaboration is important in this context as research agendas are likely to exceed the boundaries of a single R&D consortium; (III) in contrast to earlier studies (e.g., Gulati, 1995), both the consortium's start and end are reported, allowing for fine-grained examination of the timing of repeated collaboration; (IV) available data allow tracing the timing of repeated collaboration 5 years after the consortium's start and 5 years after its end; and (V) variance in consortium composition allows examining distinct types of repeated collaboration.

Although the participation of industry members is mandatory, the choice of whom to select is not prescribed. Consequently, the consortia vary in their goals, number and type of members, duration, and application area. Accordingly, the academic consortium leader can repeat the collaboration with one or more of the industry partners in subsequent consortia. Alternatively, two or more of the industry partners can repeat their collaborations across consortia with *different* consortium leaders. These different types of repeated collaboration can come with different time norms that motivate distinct timing of repeated collaborations.

3.2. Measures

3.2.1. Repeated collaboration

Repeated collaboration is operationalized according to the taxonomy of four distinct types of repeated collaboration as a function of two dimensions: university-industry versus industry-industry; dyadic versus multipartner. The four different types of repeated collaboration – the four dependent variables of this study – are assessed with four different models. These models are combined in one stacked model, as discussed in the Modeling section (3.3). The dependent variables are binary: in a given year, repeated collaboration can occur (1) or not (0). For each year since the start of a focal consortium, the study examines the occurrence of each type of repeated collaboration. For example, university-industry multipartner repeated collaboration is observed in a given year, when three or more actors of the focal consortium, including the academic consortium leader, start a new consortium. Although organizations can participate in several subsequent or parallel consortia, only the first repeated collaboration (per type) is attributed to the focal consortium, as further discussed in the Modeling section (3.3).

3.2.2. *Time and timing*

To assess the timing of repeated collaboration, an event history analysis is used (Singer & Willett, 2003) with time as a predictor for the likelihood of repeated collaboration. The study combines two 5-year time windows, one as per the consortium start and one as per the consortium end. In this way, the consortium end is empirically assessed as a discrete point in time. Herewith, this study extends formerly used models by explicitly separating dynamics during the consortium from dynamics after the consortium.

The likelihood of repeated collaboration may develop either gradually or on a punctual basis. A prolonged period of relatively little change can be interrupted by a short episode at which the likelihood of repeated collaboration fluctuates sharply; repeated collaboration might concentrate at discrete points in time, such as the consortium's start, midpoint, or end. Theoretical arguments for a punctuated temporal process concentrate on the elapse of time during the consortium (e.g., Das & Kumar, 2007; Gersick, 1988), while after the consortium ends, a linear decline is expected due to declining momentum (Amburgey et al., 1993; Gulati, 1995). Therefore, for the 5-year time window as per the consortium start, the elapse of time is conceptualized by means of dummy variables (punctuated temporal process), while for the 5-year time window as per the consortium's end, the elapse of time is conceptualized by means of a linear term. The consortium's end is the statistical reference point; thus, for instance, positive and statistically significant dummies for years 0 and 1 indicate the timing of repeated collaboration concentrated around the consortium's start.

Several alternative conceptualizations of time are also explored, including a single linear term as per the consortium's start, a combination of a linear and quadratic term as per the consortium's start (as in Gulati, 1995), a combination of two linear terms, one as per the

consortium's start and one as per the consortium's end, and a conceptualization with dummy variables for each year as per the consortium's start and each year as per the consortium's end. However, the proposed conceptualization, with dummy variables as per the consortium's start and a linear term as per its end, both fit best to the theoretical argument for the timing of repeated collaboration, and it shows the best fit to the data. The regression equation is presented in the Modeling section (3.3).

3.2.3. Control variables

This study includes control variables for the application area (dummies), historical year of observation (dummies), the selection hazard (continuous variable), consortium size (continuous variable), and network autocorrelation (continuous variable). First, consortia are observed in seven application areas, namely, 'Instruments' (reference category), 'Electrical engineering', 'Medical technology', 'Life sciences', 'Chemistry', 'Mechanical engineering', and 'Civil engineering'. Second, the historical year of observation varies from 1981 to 2004 (reference category). Because marginal effects estimations are based on all observations in this study, the reference category has no implications for the findings. Third, consortia only qualify for repeated collaboration in case the consortium size is sufficient (e.g., at least two consortium members for industry-industry dyads). This selection hazard, sufficient consortium size, is estimated as a function of two instruments: (I) the number of industry partners with whom the consortium leader collaborated in the preceding 5 years, and (II) the number of industry partners for whom one or more consortia ended in the preceding year, in the same application area as the focal consortium. Fourth, in addition to the selection criterion, the consortium size is added to the model because additional industry partners in the focal consortium can increase the likelihood of repeated industry-industry

collaboration. Finally, to correct for nonindependence of observations, a network autocorrelation term is added to the model. Because the year observations are nested in consortia, a two-mode network autocorrelation term is used, including an ‘exposure term’ and a ‘measure of participation’, in this study the consortium size (Fujimoto, Chou, & Valente, 2011).

3.3. Modeling

This study employs a longitudinal research design to investigate the likelihood of repeated collaboration over time. Discrete nonrecurring event history analysis is used (Singer & Willett, 2003), examining the timing of the first repeated collaboration of each type. Robustness tests with recurring event history models, including all future repeated collaborations, give virtually identical time patterns. As the dependent variables of this study are binary – repeated collaboration can occur in a given year, or not – a logistic regression transformation is employed.

The data have a panel structure with within-case variance (elapse of time, observation years) and between-case variance (consortium size, application area). To address potential correlations between the four types of repeated collaboration, the study uses a stacked model, with separate panels for each type of repeated collaboration. We used an outcome-type identifier (‘nesting factor’) for the stacked structure, a time identifier for the panel structure, and consortium-outcome random effects per type of repeated collaboration to control for the nestedness of the error terms. Fixed effects are not applicable to nonrepeating event history models (Allison, 2009). To address correlations between the outcomes, heteroscedasticity-robust standard errors are clustered at the consortium level. The stacked model is essential because it also allows for computing and visualizing the marginal effects (time patterns). This visualization is needed because for logistic

regression analysis, interpreting the sign and significance of individual coefficients might lead to incorrect conclusions (Hoetker, 2007).

The regression equation is presented below. Continuous variables are labeled by (C), and dummy variables are labeled by (D). As discussed in the Measurement section (3.2), time during the consortium is represented by means of dummy variables ($\text{TIME}_{\text{YEAR } x}$), while time as per the consortium's end is represented by means of a linear term $\text{TIME}_{(\text{CONSORTIUM END}=0)}$. A logistic regression transformation is used because of the binary dependent variable. Therefore, the likelihood of repeated collaboration is $\pi(\text{REPEATED COLLABORATION}^{\text{Type A}}) = e^Z / (1 + e^Z)$, with $Z = a + (\text{D}) \text{ observation year} + (\text{D}) \text{ application area} + (\text{C}) \text{ consortium size} + (\text{C}) \text{ network autocorrelation} + (\text{C}) \text{ selection hazard} + (\text{D}) \text{ TIME}_{\text{YEAR } 0} + (\text{D}) \text{ TIME}_{\text{YEAR } 1} + (\text{D}) \text{ TIME}_{\text{YEAR } 2} + (\text{D}) \text{ TIME}_{\text{YEAR } 3} + (\text{D}) \text{ TIME}_{\text{YEAR } 4} + (\text{D}) \text{ TIME}_{\text{YEAR } 5} + (\text{C}) \text{ TIME}_{(\text{CONSORTIUM END}=0)} + v_i + w_{ij} + \varepsilon_{ijt}$.

4. Results

Table 1 shows the descriptive statistics and correlations of the consortium-level data, which serve as source data for the four transformed panel data sets, one for each dependent variable. Table 2 includes the descriptive statistics and correlations for the stacked panel dataset. Consortia include, on average, 4.2 industry partners (consortium members), in addition to the university (consortium leader), and they last, on average, 4.5 years. A single consortium can result in different types of repeated collaboration, but only if the consortium size qualifies for different types of repeated collaboration (e.g., at least 3 members for multipartner industry-industry repeats) and if different subsets of the consortium members participate in different follow-up consortia.

The likelihood of dyadic industry-industry repeated collaboration (further on IDrc: 1,140 out of 1,658 consortia, 68.8%) is higher than the likelihood of subsequent multipartner industry-industry repeated collaboration (IMrc: 427 out of 1,421 consortia, 30.0%), dyadic university-industry repeated collaboration (UDrc: 429 out of 1,845 consortia, 23.3%), and multipartner university-industry repeated collaboration (UMrc: 305 out of 1,658 consortia, 18.4%). The observed difference makes sense from a statistical point of view, as IDrc is the least constrained form of repeated collaboration (consortia include only one academic consortium leader but multiple industry members that can repeat their collaborations). The average timing of different types of repeated collaboration varies significantly as well (IDrc: 1.1 year after the consortium start; IMrc 1.9 years; UDrc 3.0 years; and UMrc 2.6 years; related standard deviations 1.8; 2.4; 2.5; 2.3). Although the timing averages suggest that industry partners repeat their collaborations earlier than university partners, further analysis is needed because the average scores may conceal a combination of early and late timing.

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 Insert Tables 1 and 2 about here

Table 3 shows the random effects logistic regression models, stacked for the different types of repeated collaboration (UDrc; IDrc; UMrc; and IMrc). Model comparison, based on log-likelihood ratio tests (χ^2) for nested models and on the Akaike information criterion (AIC) for nonnested model comparison, shows that the model presented in Table 3 fits the data better than alternative model specifications; it fits better than the baseline model with only control variables ('Model improvement' in Table 3; $p < 0.001$), it fits better than models with alternative conceptualizations of time (see 3. Methodology section), and it is more parsimonious than the general model with dummy variables for all time points ($p > 0.100$).

Further inspection of the results per outcome type reveals that the likelihood of UDrc is lower at the consortium's start and during the consortium relative to the consortium's end, although the difference is not statistically significant. The likelihood of UDrc drops statistically significantly ($p < 0.010$) after the consortium's end. Additional tests show that this specific type of repeated collaboration can also be modeled adequately with a linear time conceptualization (0.132 ; $p < 0.050$) in combination with a quadratic term (-0.018 ; $p < 0.050$). This means that from the start of the consortium, the likelihood of UDrc increases during the first ca. 3.7 years, approaching the consortium's end, after which the likelihood of UDrc decreases. The findings are in line with our hypothesis. The results for UDrc are very similar to the findings of Gulati (1995), who observed the highest likelihood ca. 3.8 years after the consortium's start.

The likelihoods of both IDrc and IMrc are statistically significantly ($p < 0.001$) higher at the consortium's start relative to the consortium's end. In line with our hypothesis, they show a strong decline after the consortium's start. The likelihood of UMrc is not statistically significantly lower or higher at the consortium's start compared to its end. However, it is significantly lower both during and after the consortium.

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 Insert Table 3 about here

In logistic regression models, all variables in the model affect the estimated effects (Hoetker, 2007). A proper interpretation of these coefficients requires the computation of average marginal effects by means of the observed values for all variables in the model. To explore the timing of repeated collaboration, Bonferroni-adjusted post hoc tests are applied to estimate to what extent the predicted probability in a given year differed from the likelihood of repeated collaboration in the year of the consortium's start and/or end.

Figure 3 visualizes the predicted probabilities based on the average marginal effects as well as the 95% confidence interval. It is important to note that the range on the y-axis varies for the different types of repeated collaboration due to the variance in the general likelihood of repeated collaboration (subsequently 23.3%, 68.8%, 18.4%, and 30.0% for UDrc, IDrc, UMrC, and IMrc). In addition, for all types of repeated collaboration, the likelihood per year looks relatively small, as the total likelihood is stretched over multiple years of observation. Figure 3 also includes the random chance of observing the respective type of repeated collaboration in a given year. For all types of repeated collaboration, the observed chance is much higher than the random chance, i.e., the observed time patterns are not random.

Figure 3 shows that the likelihood of UDrc gradually increases between the consortium's start and end (from 3.3% to 4.2%) and decreases statistically significantly ($p < 0.050$) after the consortium's end (from 4.2% to 1.9% 5 years after the end). In line with our hypothesis, the results show sequential timing of UDrc. The likelihood of IDrc, on the other hand, is highest at the consortium's start (32.5%) and then declines significantly (to 13.2% at the consortium's end, 3.1% 5 years after the consortium's end, $p < 0.001$). The likelihood of IMrc follows an identical pattern; it is the highest at the consortium's start (10.4%) and then declines significantly (to 3.4% at the consortium's end and 1.2% 5 years after the end, $p < 0.001$). In line with our hypothesis, the results show parallel timing of IDrc and IMrc. Finally, the likelihood of UMrC follows a different pattern with two peaks, one around the consortium's start (3.4% at the consortium start, 3.9% at year 1) and one around its end (3.8%, at the end, 4.7% at year 5), with a dip in between the peaks (1.5% at year 3) and a strong decline after the consortium's end (to 0.4% 5 years after the consortium end). While there is no statistically significant ($p > 0.100$) difference in the likelihood of UMrC at

the consortium's start versus its end, the dip at year 3 is statistically significant ($p < 0.05$), as is the decline after the consortium's end ($p < 0.001$).

Bonferroni-adjusted pairwise comparisons across types of repeated collaborations confirm that at the year of the consortium's start, the relative likelihood ratios of IDrc and IMrc are statistically significantly ($P < 0.001$) *higher* compared to UDrc and (marginally) significantly higher than the likelihood of UMrc. Conversely, at the consortium's end, the relative likelihoods of UDrc and UMrc are statistically significantly ($p < 0.010$) higher than those of IDrc and IMrc, confirming our hypothesis.

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 Insert Figure 3 about here

4.1. Interview results

To substantiate the observed patterns of the timing of repeated ties, 51 interviews were conducted with a stratified sample of university partners (13) and industry partners (38) who participated in consortia in the Dutch water sector (16% of the sector; 1.6% of all actors in the dataset). During these interviews, the consortia's composition, dynamics, and outcomes were discussed, particularly the motives for parallel versus sequential timing of repeated collaboration. All interviews were transcribed verbatim, after which relevant text fragments were analyzed by means of open coding, axial coding, and selective coding. The analysis resulted in three motives for parallel timing and three motives for sequential timing. Table 4 shows the motives and the percentage of respondents that mentioned each motive.

Parallel timing is particularly associated with gaining knowledge breadth (mentioned by 31% of the interviewed university partners), synergy (34% of the industry partners), and first-mover advantages (24% of the industry partners). Regarding knowledge breadth, a respondent

argued: *“If you are doing things at the same time, then you can broaden the scope and address multiple types of questions”* (Resp.1). Parallel consortia can foster synergistic benefits in the form of mutual learning: *“There is a great benefit of having two [consortia in parallel], because then they [the research associates] learn a lot from each other [...] they will exchange ideas and they will help each other”* (Resp. 2). The following illustrates these synergy benefits: *“A great example, not just because they were in parallel, but the two consortia really understood each other [...]. During the presentations, the left half of the slides showed the experiment results and the right half the numerical calculations. That was a delightful work and extremely useful for us”* (Resp. 3). Parallel timing is also motivated by first-mover advantages related to the critical mass needed to scale up: *“It's very nice to have a certain critical mass [...] not in a single project but in adjacent projects, with similar partners”* (Resp. 4), and the urgency to speed up and ‘compress time’: *“Some things have to be done simultaneously, because if you do them successively, you are going to lag behind”* (Resp. 5); *“In our case it is more or less demand driven [...], in case there is something very urgent, we end up with starting a lot of projects simultaneously”* (Resp. 6).

Sequential timing of repeated collaboration is associated with gaining knowledge depth (mentioned by 38% of the interviewed university partners), learning and evaluative insights over time (55% of the industry partners), and feasibility (69% of the university partners and 47% of the industry partners). Follow-ups are initiated to gain knowledge depth and ‘extend time’: *“The main advantage is that, because you actually never get as far as you would like, it's nice to be able to do follow-up research and to apply the new insights”* (Resp. 4). Sequential timing enables learning: *“The main advantage [of sequential consortia] is that partners develop joint routines and become more and more effective, [...] because you know exactly what you can expect, what you can ask, what you should ask, and what others can do. That takes time”* (Resp. 7). In addition, this timing

of repeated collaboration is motivated by evaluative insights: “*By the time the consortium comes to an end, you discuss the successful completion, the utility, the successful collaboration. A normal question that then comes up is whether we can find a way to continue [the consortium]*” (Resp. 8); “*You particularly look at what has been learned and how to continue with new questions that have emerged*” (Resp. 1). Finally, feasibility is central to the preference of sequential timing over parallel timing: “*Internally we always evaluate our portfolio of R&D projects; is it feasible to join now or is it wise to wait a year before starting something new [...] in terms of the number of current projects, the required capacity, and our available capacity*” (Resp. 9).

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 Insert Table 4 about here

5. Conclusion and Discussion

This study aimed to unpack the single most prominent barrier to university-industry collaboration: the tension of divergent time norms (e.g., Bruneel, 2010; Dille & Söderlund, 2011; Meyer-Krahmer & Schmoch, 1998; Reilly et al., 2016). As in many types of cross-sectoral collaboration, university and industry have fundamentally different understandings of when things should be done. Whereas university partners take time for learning and goal completion in a way that mirrors the time they generally have available to finish PhD projects, industry partners face pressures for early responses due to rivalry and time-to-market dynamics (e.g., Bjerregaard, 2010; Niedergassel & Leker, 2011). To unpack the time-norm tension, we examined when university-industry consortia choose to repeat their collaboration in a second consortium. Through repeated collaborations, involved parties can shift the time focus in their favor, either “compressing time” by starting multiple consortia in parallel or “extending time” by means of sequentially timed consortia. Indeed, this study reveals that industry predominantly pursues a *time compression*

strategy associated with gaining knowledge breadth through lateral projects, synergy, and first-mover advantages in terms of critical mass to scale up and speed up. University partners, on the other hand, pursue a *time extension strategy* associated with gaining knowledge depth by means of follow-up projects, learning and evaluative insights over time, and feasibility in terms of staff capacity, continuity, and available funding. In multipartner university-industry consortia, both time-utilization strategies coexist instead of blending; this observation signals how difficult it is to resolve the time-norm tension.

While previous research on university-industry collaboration argued that gaining mutual experience can reduce collaboration barriers and increase innovation outcomes (e.g., Bruneel et al., 2010; Perkmann et al., 2013, Szücs, 2018), distinct timing preferences of university and industry partners must first be addressed before such mutual experiences can be effectively acquired. While prior research mainly focused on sequential timing and ignored the option of parallel timing, it is rather striking that the proportion of parallel-timed repeated ties far exceeds the proportion of sequentially timed repeated ties in our research setting (80.7% vs. 19.3%).

Moreover, the innovation outcomes of both time-utilization strategies are quite different. In our research setting, the innovation outcomes of all studied consortia are evaluated by external expert committees, appointed by the technology program. Post hoc analyses show that consortia resulting from repeated university-industry collaboration have a statistically significantly higher likelihood of innovation outcomes ($\Delta+15.3\%$) relative to one-off consortia (on average 41.4% - reference category) or relative to consortia resulting from repeated industry-industry collaboration ($\Delta-2.6\%$). However, these innovation outcomes are conditional on the timing of repeated ties. The superior innovation outcomes of repeated university-industry collaboration mainly result from sequentially timed consortia ($\Delta+17.5\%$), while the innovation benefits of parallel-timed consortia

are much smaller ($\Delta+8.6\%$) and not significantly different from one-off consortia. The post hoc analyses highlight the value of the university's time extension strategy relative to the industry's time compression strategy. Based on our interviews, we conclude that time compression strategies aim at the rapid exploitation of opportunities and hedging your bets, while time extension strategies aim at the patient and cautious build-up of shared competences to strengthen the consortium. Obviously the latter strategy has a better pay-off as it indeed leads to a higher likelihood of innovation outcomes. Accordingly, this study showed how the time-norm tension manifests itself in the collaborative behavior of actors. Yet our study also reveals that there is no simple universal solution to address the tension, because the pursuit of a single innovation until it can be commercialized might simply take too long for many industry partners, particularly in fast-changing environments.

We underline the importance of a temporal perspective on interorganizational collaboration in general, as called for by several researchers (e.g., Ahuja, Soda, & Zaheer, 2012; Zaheer et al., 1999), and on university-industry collaboration in particular (e.g., Hmieleski & Powell, 2018, Perkmann et al., 2013). We would like to reemphasize this call and suggest the following directions for future research. First, this study has demonstrated that distinct time norms of university and industry result in very different time-utilization strategies. Although additional qualitative interviews were conducted to substantiate the time-utilization strategies, future research should investigate in greater detail the substantive processes underlying these distinct strategies of time use. Second, the study was conducted in a very specific empirical setting in which organizations collaborate in time-bound research consortia to achieve formally stated goals. Although publicly funded university-industry collaborations are relatively frequent and prominent (e.g., Szücs, 2018), repeated collaboration between university and industry partners is a topic of multiple

studies (e.g., Bruneel et al., 2010; Hewitt-Dundas et al., 2019), and as the average consortium lifespan of 4 to 5 years matches the average duration of PhD projects, future research should identify the scope conditions under which the observed time-utilization strategies manifest themselves in collaborative behavior. The findings in this paper provide evidence that collaborating actors that are subject to different time norms can use repeated collaboration strategies to have their own time preferences prevail. Future research should investigate to what extent the results and strategies discovered here also hold, for example, for individual actors and in other (research) contexts. Finally, variance in time-utilization strategies is not only indicative of different relational processes but also adds up to different innovation network structures. We therefore call for research that examines the network-level consequences of time-utilization strategies and that provides guidance to policy makers for managing such innovation networks. This, we believe, is an exciting perspective for research policy and management studies.

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Tables

Table 1

Descriptive statistics and correlations – Consortium level

Variables	Mean	SD	1	2	3	4	5	6
1 University-industry dyadic RC	0.233	0.423	1					
2 Industry-industry dyadic RC	0.688	0.464	0.042†	1				
3 University-industry multipartner RC	0.184	0.388	0.231***	0.142***	1			
4 Industry-industry multipartner RC	0.300	0.459	-0.018	0.326***	0.114***	1		
5 Consortium size	4.243	2.733	-0.030	0.296***	0.119***	0.323***	1	
6 Consortium duration	4.459	1.408	0.005	0.080**	0.051*	0.085**	0.247***	1

Note: Subsequently, 1,845, 1,658, 1,658, and 1,421 observations on repeated collaboration.

† $p < 0.100$, * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$.

Table 2

Descriptive statistics and correlations – Stacked panel dataset

Variables	Mean	SD	1	2	3	4	5	6	7
1 University-industry dyadic RC	0.011	0.105	1						
2 Industry-industry dyadic RC	0.030	0.170	-0.019***	1					
3 University-industry multipartner RC	0.008	0.089	-0.010†	-0.016**	1				
4 Industry-industry multipartner RC	0.011	0.105	-0.011*	-0.019***	-0.010†	1			
5 Consortium size	4.410	2.341	-0.005	0.068***	0.040***	0.094***	1		
6 Network autocorrelation	0.165	0.269	0.003	0.270***	-0.003	0.050***	0.098***	1	
7 Selection hazard	0.256	0.168	-0.103***	-0.019***	-0.005	0.093***	0.007	-0.014**	1
8 Time year 0	0.171	0.376	0.006	0.195***	0.012*	0.068***	0.079***	0.074***	-0.050***
9 Time year 1	0.136	0.343	0.009†	0.011*	0.024***	0.011*	0.028***	0.044***	-0.035***
10 Time year 2	0.114	0.318	0.002	-0.021***	-0.004	-0.001	0.014**	0.013**	-0.019***
11 Time year 3	0.091	0.288	0.002	-0.021***	-0.011*	-0.007	0.014**	0.003	-0.015**
12 Time year 4	0.045	0.207	0.002	-0.026***	0.009†	-0.004	0.022***	-0.013*	-0.012*
13 Time year 5	0.014	0.118	0.004	-0.013*	0.014**	-0.004	0.028***	-0.012*	0.001
14 Time (Consortium end=0)	0.928	1.532	-0.024***	-0.090***	-0.036***	-0.042***	-0.102***	-0.068***	0.081***
Variables (continued)			8	9	10	11	12	13	14
8 Time year 0			1						
9 Time year 1			-0.180***	1					
10 Time year 2			-0.163***	-0.142***	1				
11 Time year 3			-0.144***	-0.126***	-0.113***	1			
12 Time year 4			-0.099***	-0.086***	-0.078***	-0.069***	1		
13 Time year 5			-0.054***	-0.047***	-0.043***	-0.038***	-0.026***	1	
14 Time (Consortium end=0)			-0.275***	-0.240***	-0.217***	-0.192***	-0.131***	-0.072***	1

Note: In total, 38,391 observations across 4 panels. Per type of repeated collaboration, panels with subsequently 12,365, 6,262,

11,128, and 8,636 observations on 1,845, 1,658, 1,658, and 1,421 consortia. † $p < 0.100$, * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$.

Table 3. Logistic regression of likelihood repeated collaboration

	University-industry dyadic RC		Industry-industry dyadic RC		University-industry multipartner RC		Industry-industry multipartner RC	
Intercept	0.840*	(0.424)	-3.418***	(0.262)	-0.311	(0.436)	-0.409	(0.405)
Consortium size	-0.001	(0.022)	0.240***	(0.029)	0.102***	(0.021)	0.213***	(0.031)
Network autocorrelation	0.959***	(0.190)	1.278***	(0.107)	0.644*	(0.262)	1.079***	(0.176)
Selection hazard	-11.875***	(2.464)	1.579*	(0.633)	-1.334	(0.929)	0.084	(0.516)
Time year 0	-0.258	(0.176)	1.350***	(0.183)	-0.120	(0.196)	1.275***	(0.204)
Time year 1	-0.214	(0.177)	0.490**	(0.180)	0.041	(0.191)	0.571**	(0.215)
Time year 2	-0.322†	(0.190)	0.095	(0.191)	-0.581*	(0.232)	0.334	(0.233)
Time year 3	-0.287	(0.201)	0.132	(0.200)	-0.966**	(0.284)	0.179	(0.254)
Time year 4	-0.223	(0.255)	-0.340	(0.312)	-0.093	(0.270)	0.198	(0.315)
Time year 5	0.120	(0.381)	-0.044	(0.482)	0.238	(0.362)	-0.094	(0.558)
Time (Consortium end=0)	-0.167**	(0.052)	-0.344***	(0.065)	-0.463***	(0.077)	-0.217**	(0.071)
Observations	12348		6252		11079		8605	
Consortia	1845		1658		1658		1421	
Log likelihood	-6779.038							
model fit	2810.240***							
Df	155							
Model improvement	209.910***							

Notes: In total 38,284 observations. Controlled for application area and observation year. Standard errors in parentheses.

† $p < 0.100$, * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$.

Table 4

Motives for parallel vs. sequential timing of repeated collaboration (% of university and industry partners that mentioned the motive)

Timing	Motive	University	Industry
Parallel	Gaining knowledge breadth	31%	26%
	Synergy	8%	34%
	First-mover advantages	15%	24%
Sequential	Gaining knowledge depth	38%	34%
	Learning and evaluative insights over time	23%	55%
	Feasibility	69%	47%

Figures

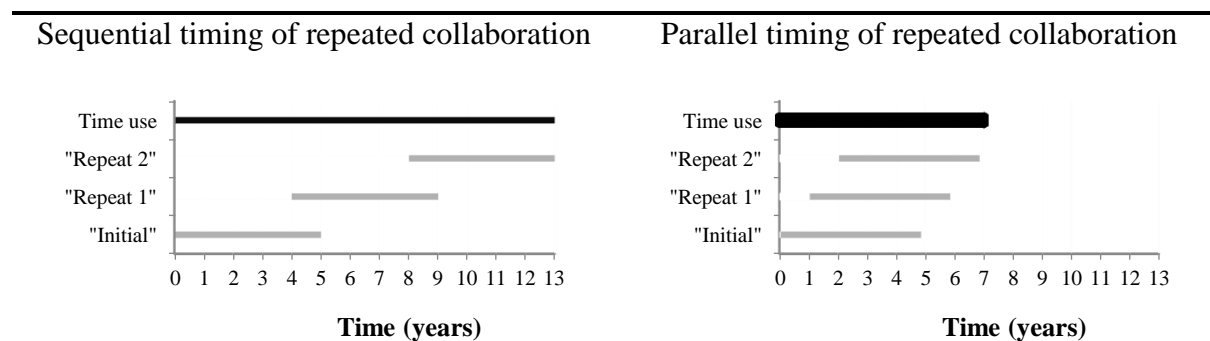


Fig. 1. Timing of repeated collaboration

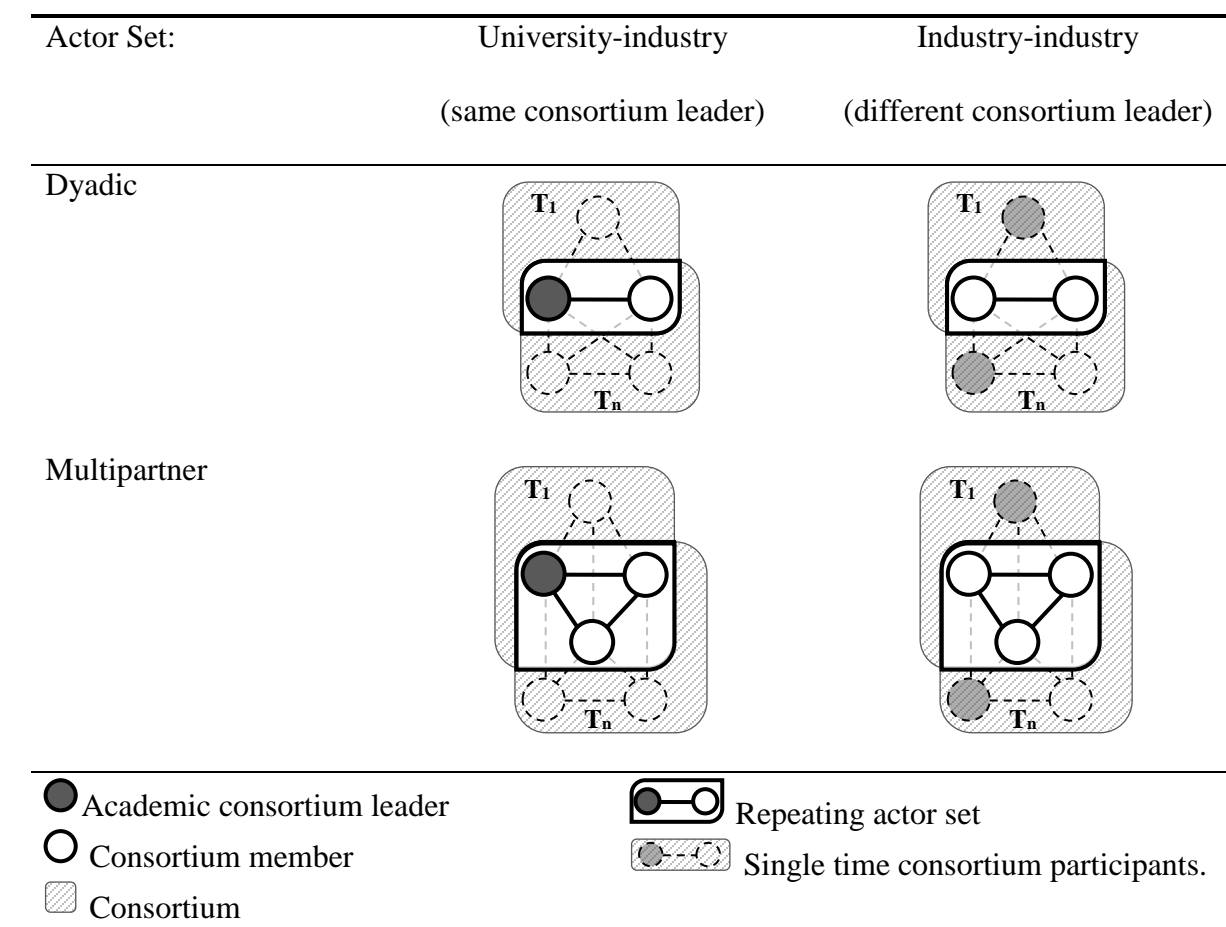


Fig. 2. Actor sets involved in repeated collaboration

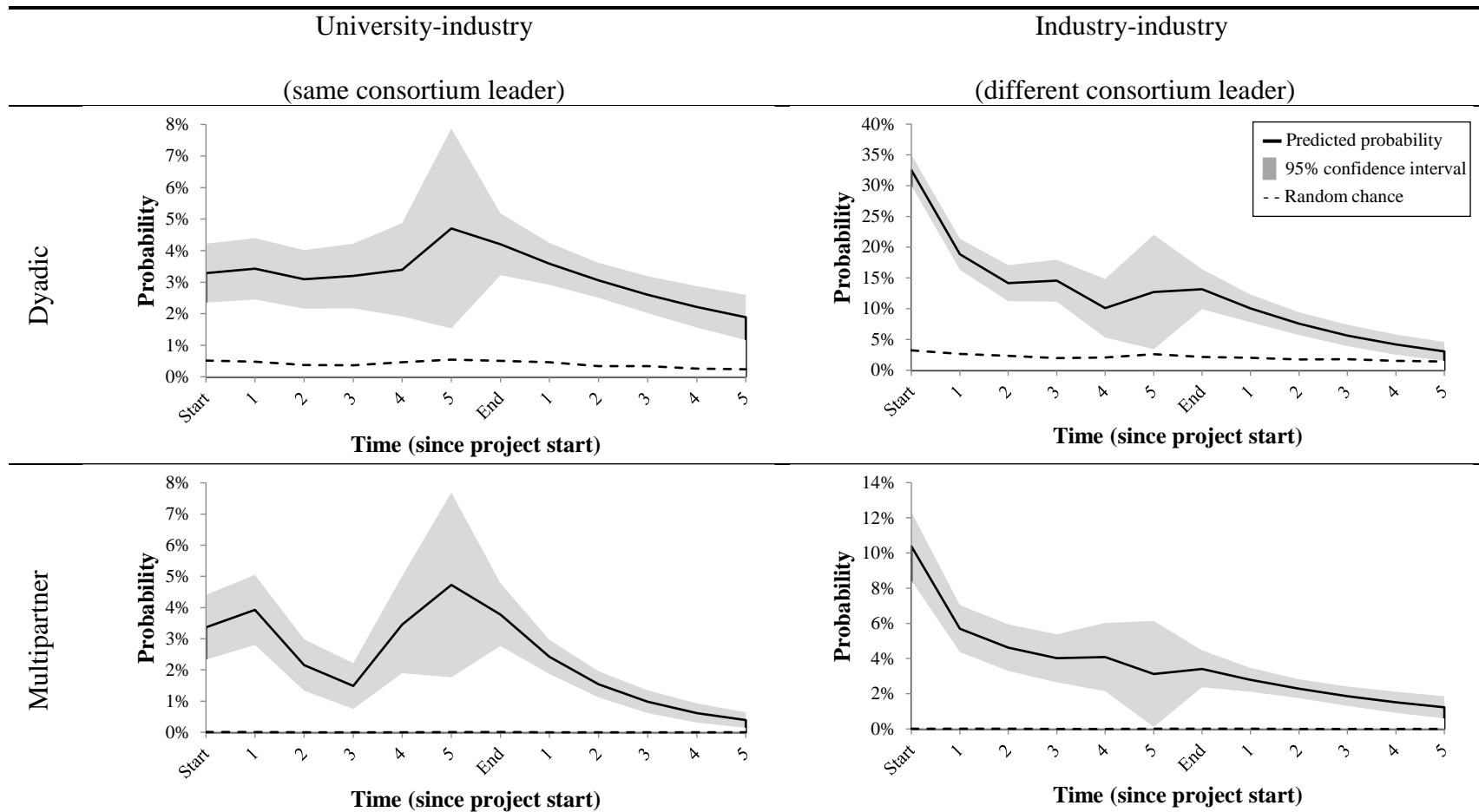


Fig. 3. Observed time patterns in repeated collaboration (Average marginal effects)